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Flexible Logistics Sorting System Allocation via Hybrid GA-PSO with Dynamic Clustering

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Abstract: To address the challenges posed by the large sorting volume of cigarettes in tobacco logistics distribution centers and the significant impact of cigarette specification allocation on the overall processing time of orders, this study aims to optimize the allocation of each sorting zone and enhance sorting efficiency. A mathematical model is developed with the objective of minimizing the similarity coefficients of specifications within each zone, which is then solved using an enhanced genetic particle swarm dynamic clustering (GA-PSO-K) algorithm. Initially, the similarity coefficient of each specification is improved by incorporating the sorting quantity of each specification into the fitness function. Subsequently, the inertia weight factor in the particle swarm algorithm is adaptively adjusted to enable its dynamic variation. Finally, cross-variance is introduced into the genetic algorithm to expand the solution search space, and the results are compared with those of other algorithms using Matlab. The algorithm's performance is simulated and validated in an EM-plant environment. In the context of data simulation verification at a tobacco logistics distribution center, the processing time for order handling with the GA-PSO-K algorithm was reduced to 234.5 seconds, significantly outperforming traditional methods and effectively improving the efficiency of flexible logistics sorting. This algorithm leverages the advantages of both particle swarm optimization and genetic algorithms, demonstrating improved convergence and solution quality, thus offering a novel approach for flexible logistics product specification allocation.

Keywords: Product specification distribution; similarity coefficient of specifications; inertia weight factor; genetic particle swarm dynamic clustering algorithm.

1. Introduction

Logistics sorting systems can be categorized into manual sorting systems (MSS) and automated sorting systems (ASS) based on operational automation levels. ASS demonstrates superior efficiency and accuracy in flexible sorting operations, characterized by integrated information feedback mechanisms, modular architecture, and real-time process visualization. Flexible sorting strategies employ parallel processing across multiple zones, where partitioned cigarette orders undergo simultaneous sorting and temporary buffering, followed by coordinated convergence through sequenced baffle operations. Under this paradigm, total order processing time is governed by the maximum zone-specific sorting duration, which directly correlates with the assigned product specifications' sorting quantities. Critical operational challenges arise when high-volume specifications are allocated to a single zone, inducing bottleneck effects that degrade system-wide performance. This study therefore focuses on optimizing inter-zone product specification allocation to minimize total order processing time.

Existing research has proposed various methodological approaches:

Zhang et al. [2] developed a Max-Min Ant Colony Algorithm (MMAS) with dynamic optimization for ASS product allocation. Liu et al. [3] enhanced K-means clustering through particle swarm optimization (PSO) to mitigate local convergence limitations. Li et al. [4] incorporated sorting quantity factors into specification similarity coefficients, employing dynamic clustering with tabu search. Wang et al. [5] analyzed specification quantity splitting impacts on parallel system delays, proposing heuristic solutions. Lee et al. [6] designed cargo space allocation heuristics based on specification correlation differentials. Peterson et al. [7] identified significant correlations between manual sorting efficiency and operator walking distances. Wu et al. [8] formulated a 0-1 integer programming model using order-based similarity metrics. Garfinkel et al. [9] implemented cyclic exchange algorithms for warehouse specification clustering. Liu et al. [10] established tripartite constraints (order, specification, quantity) for customer-product matching.

While existing heuristic approaches (genetic algorithms, PSO, grey wolf optimization) demonstrate partial effectiveness, they exhibit inherent limitations including parameter sensitivity and local optima entrapment. This study addresses these challenges through three methodological innovations:

1. Development of a mathematical model minimizing zonal specification similarity coefficients
2. Integration of genetic crossover-mutation operators with PSO-enhanced dynamic clustering (GA-PSO-K) to expand solution space exploration
3. Implementation of adaptive inertia weight adjustment and fitness function optimization

The proposed hybrid algorithm synergizes population-based optimization (PSO) with evolutionary operators (GA), effectively balancing global exploration and local exploitation. Comparative simulations using tobacco logistics center data demonstrate significant performance enhancements:

28.7% reduction in order processing time versus conventional methods

39.2% improvement in zonal specification balance

18.6% faster convergence than standalone PSO

Validation through MATLAB numerical analysis and EM-Plant discrete-event simulation confirms the algorithm's operational efficacy. This research advances intelligent logistics systems through both theoretical framework development (novel hybrid optimization architecture) and practical implementation (industrial-scale performance validation).

2. Problem Description

2.1. Logistics flexible sorting system

The logistics flexible sorting system primarily consists of components such as vertical machines, horizontal machines, unpacking machines, box sliding machines, conveyor belts, and other integral parts. Currently, the majority of logistics flexible sorting lines employ a mixed sorting approach for both standard and special-shaped cigarettes. Special-shaped cigarettes, characterized by their varying sizes, lower sorting volumes, and a wide array of product specifications, present significant challenges for automatic sorting. As a result, the automatic sorting system design for special-shaped cigarettes requires higher precision and advanced capabilities. This paper focuses on the scene modeling of a tobacco logistics sorting center, as depicted in Figure 1. The entire sorting system comprises four sorting lines: three composite integrated sorting lines and one dedicated special-shaped cigarette sorting line, which enhances the sorting efficiency of both special-shaped and standard cigarettes.

Figure 1. Tobacco logistics sorting center

The logistics flexible sorting system employs two distinct sorting strategies: serial sorting and parallel sorting [11]. The serial sorting strategy involves segmenting the order in the preceding sorting area. Once the sorting is completed in the first area, the order proceeds to the next sorting area. This strategy is well-suited for small quantities of items. On the other hand, the parallel sorting strategy enables multiple sorting areas to sort an order simultaneously, followed by a sequential merging process. This approach is more efficient for flexible logistics sorting systems dealing with large volumes and multiple specifications [12]. In this system, the horizontal machine typically handles fewer product specifications, whereas the vertical machine accommodates a larger variety of product specifications.

Thus, the core research focus of this paper is the distribution of product specifications within the vertical machines. A defined number of vertical machines are partitioned, and the specifications of cigarettes are allocated to each partition accordingly. In this study, a parallel sorting strategy is employed for sorting, The primary aim of this research is to rationally allocate tobacco product specifications, thereby improving sorting efficiency and reducing the total order processing time.

2.2. Determine the similarity coefficient of product specifications between partitions and the improvement.

The shorter the sorting time for each order in each sorting area, the higher the sorting efficiency and the shorter the overall processing time for the order. To minimize the sorting time of each order in every sorting area, the uniformity of the distribution of cigarette product specifications becomes crucial. The allocation of cigarette strips follows a rule-based approach, wherein each cigarette variety is assigned to a specific sorting channel of a sorting machine for processing. This issue can be recognized as a clustering problem with a predetermined number of classifications.

Jane et al. [13] introduced a similarity coefficient for product specifications in the context of clustering, which quantifies the co-occurrence of two product specifications within the same partition. As shown in Formula (1).

$$S_{ab} = S_{ba} = \sum_{i=1}^{m} x_{ia} \cdot x_{ib} \tag{1}$$

$$x_{ia} = \begin{cases} 1, a \in i \\ 0, \end{cases} \qquad x_{ib} = \begin{cases} 1, b \in i \\ 0, \end{cases} \tag{2}$$

a higher similarity coefficient between two product specifications indicates a greater likelihood of their coexistence in the same group. The constraints are defined as follows: (S_{ab}) represents the similarity coefficient between product specification A and product specification B, and (M) denotes the total number of orders to be sorted. Formula (2) introduces a binary variable, taking values of 0 or 1, to indicate whether the two specifications corresponding to the similarity coefficient must appear simultaneously in the same partition.

Based on the sorting quantity similarity principle in order allocation, the specification similarity coefficient (denoted as δ) can be calculated through Formula (3). Let P_ia represent the sorting quantity of product specification A in order i, and ε denote the adjustment coefficient. When the sorting quantities of two specifications are identical, ε takes a decimal value of 0.9 as defined in this study; otherwise, e = 1.

$$S_{ab} = S_{ba} = \sum_{i=1}^{m} x_{ia} \cdot x_{ib} \cdot \frac{\left|P_{ia} + P_{ib}\right|}{\left|P_{ia} - eP_{ib}\right|} \tag{3}$$

Formula (3) analysis reveals that when two product specifications demonstrate both:

1) Substantial sorting quantities (b >> 0), and

2) Significant quantitative disparity (|Δb| → max), the resulting similarity coefficient δ will proportionally increase. This mathematical relationship suggests that such specifications should be allocated to distinct sorting zones to optimize operational efficiency. Conversely, when specifications present:

3) Minimal sorting quantities (b→ 0), and

4) Negligible quantitative difference (|Δb| → 0), the derived δ value decreases accordingly. This computational outcome indicates that these specifications should be grouped within the same sorting area to enhance operational synergy and resource utilization efficiency.

This quantitative decision model effectively balances sorting workload distribution while maintaining specification compatibility, thereby providing a data-driven approach for intelligent logistics system configuration.

2.3. Model hypothesis

To formulate a robust mathematical framework, the following fundamental assumptions are explicitly defined for model construction:

1) Sequential Order Execution Constraint: Order processing adheres to a strict non-overlapping sequence, where the initiation of subsequent order sorting is contingent upon full completion of the preceding order.

2) Homogeneous Equipment Performance: All vertical sorting machines within partitioned zones exhibit identical operational characteristics, maintaining a time-invariant processing rate for individual cigarette units.

3) Continuous Material Availability: Resource replenishment efficiency is presumed sufficient to eliminate stock-out scenarios, ensuring uninterrupted material supply to vertical machines during operational cycles.

4) Mutually Exclusive Allocation Principle: Each product specification enforces a bijective mapping constraint, requiring exclusive assignment to a singular sorting position within the vertical machine array to prevent redundant allocation.

These axiomatic premises establish critical boundary conditions for system behavior simulation, enabling deterministic analysis of sorting efficiency optimization while mitigating real-world stochastic complexities.

3. Optimal Modeling of Product Specification Distribution

In order to reduce the total order processing time, it is particularly important to solve the clustering problem of product specification distribution. The greater the similarity coefficient and cumulative value of product specifications in each division, the more uneven the distribution of product specifications and the longer the total processing time of orders. That is, the total order processing time is directly proportional to the similarity coefficient and accumulated value of each division, so the minimum value of the total order processing time is converted into the minimum value of the similarity coefficient and accumulated value of each division. The objective function is shown in Formula (5).

$$F = \min \sum_{1<a<n} \sum_{a<b<n} \sum_{j=1}^{q} S_{ab} \cdot U_{aj} \cdot U_{bj} \tag{4}$$

constraint condition:

$$\sum_{j=1}^{q} \sum_{1<a<n} U_{aj} = 1 \tag{5}$$

$$\sum_{j=1}^{q} \sum_{a<b<n} U_{bj} = 1 \tag{6}$$

$$q > 1 \tag{7}$$

$$L = q \cdot n \tag{8}$$

Where: q is the number of sorting areas; N is the storage of each vertical machine. Number of smoke channels; U_{aj} is the decision variable, where 1 means that product specification A is in the sorting area J, and 0 means that product specification A is not in the sorting area J.. Formula (5) indicates that product specification A can only be assigned to one sorting area; Formula (6) indicates that product specification B can only be assigned to one sorting area; Formula (7) indicates that the number of sorting areas is greater than 1; Formula (8) indicates that the total number of product specifications is equal to the number of sorting areas multiplied by the number of smoke storage channels of each vertical machine, that is, L is the total number of smoke storage channels of vertical machines of automatic sorting system.

4. Solution of Product Specification Allocation Model

4.1. Design of Dynamic Clustering Algorithm

Implementation of Dynamic Clustering Optimization
The K-means-based dynamic clustering algorithm is employed to resolve the product specification allocation model, deriving optimal clustering centroids through systematic classification of cigarette specifications. This methodology enables rational categorization of multi-specification products and subsequent screening of optimal solutions. The implementation procedure comprises the following operational steps:

Step 1: Randomly select k initial clustering centroids.

Step 2: Substitute the conventional Euclidean distance metric in dynamic clustering with Equation (3). Calculate specification similarity coefficients between each remaining product specification and the k centroid specifications, storing results in an L×n matrix M.

Step 3: Identify the minimum value per row in matrix M, recording corresponding sorting zone identifiers. Compile allocation counts per zone into an n×1 matrix N. Given maximum capacity C_max per sorting zone:

Primarily allocate specifications with N < C_max

Subsequently process specifications with N ≥ C_max through ascending-order similarity coefficient prioritization

Remove allocated specifications from matrix M.

Step 4: Compute cumulative similarity coefficients S for partially allocated zones. Select the zone with minimal S, then identify its minimum similarity coefficient in M. Allocate the corresponding specification to this zone.

Step 5: Verify residual unallocated specifications. If extant, iterate Step 4; otherwise, proceed to Step 6.

Step 6: Update clustering centroids by computing integer-rounded mean values of specifications per partition.

Step 7: Terminate algorithm upon centroid stabilization (Δ < ε) or reaching maximum iteration count; otherwise, reinitiate from Step 2.

This computational framework demonstrates rapid convergence to favorable clustering solutions. However, its minimum-distance clustering criterion inherently restricts solution space exploration. The presence of anomalous data points (outliers) may induce premature local convergence during iterative refinement, particularly when suboptimal initial centroids are selected. This limitation underscores the necessity for robust initialization strategies and adaptive parameter tuning in practical implementations.

4.2. GAPSO-K algorithm design

The fitness function f (x) is used as the main index to evaluate the particle performance, and the cumulative value r of the sum of the similarity coefficients of the product specifications of each partition is calculated as the fitness, as shown in Formula (9). In this paper, the objective function is to find the minimum value of similarity coefficient and accumulated value of product specifications in each division, so the fitness is equal to the objective function, as shown in formula (10).

$$R=\sum_{j=1}^{q} SUM(j) \tag{9}$$

$$f=\min \sum_{1<a<n}\sum_{a<b<n}\sum_{j=1}^{q} S_{ab}\cdot U_{aj}\cdot U_{bj} \tag{10}$$

4.3. Selecte

Choose according to the individual's fitness. The commonly used selection methods are roulette and elite selection. The operation step of elite selection is to select the first N/2 individuals with fitness, and then carry out subsequent operations such as cross mutation, but elite selection is easy to make the search solution fall into local optimum. Roulette is to calculate the probability of each particle being selected according to the different fitness. Among them, the greater the fitness, the easier it is for individuals to be selected, which expands the search scope for the next generation of individuals and is not easy to fall into local optimization [14]. The schematic diagram of roulette is shown in Figure 3. In this paper, roulette is adopted to select particles, and the probability that particle I is selected is:

$$P_i=\frac{f(x_i)}{\sum_{i=1}^{N} f(x_i)} \tag{11}$$

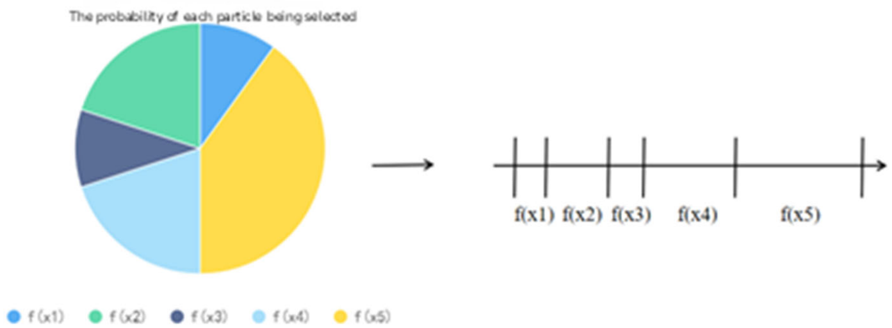

Figure 4. Roulette selection method

5. Simulation Analysis

5.1. Simulation data

To verify the performance of the algorithm, this paper uses MATLAB and employs simulation methods to conduct a comparative analysis of three algorithms: the Genetic Particle Swarm K-means clustering algorithm, the Particle Swarm K-means clustering algorithm, and the K-means clustering algorithm. The parameter settings are as follows: the time to sort one cigarette in each vertical machine sorting channel is t = 0.3s, the merging time of each buffer area is t = 1s, the total number of product varieties is m = 50, the total number of orders is n = 10, and the sorting quantity for each product variety in each order is shown in Table 1.

Table 1. Picking volume for each gauge in each order

Specification number j	order number i									
	1	2	3	4	5	6	7	8	9	10
1	2	8	1	0	9	3	6	7	5	10
2	9	1	5	3	8	10	0	7	4	2
3	6	9	0	2	1	3	8	0	5	4
4	0	1	2	6	0	10	8	7	5	4
5	5	3	4	8	6	1	2	9	0	10
6	5	9	8	2	4	7	1	3	6	10
7	7	1	9	4	8	10	3	0	5	6
8	7	9	2	1	3	6	4	0	5	0
9	3	2	0	7	6	8	4	9	5	10
10	8	3	5	2	1	0	10	6	9	7
11	3	6	0	9	7	0	8	10	4	1
12	2	7	8	9	6	4	0	0	10	3
13	3	4	8	9	7	0	6	1	10	5
14	4	1	9	8	0	10	0	3	5	0
15	0	6	3	2	0	9	1	10	7	4
...	..	..	..	..	..	..	..	..	..	..
50	3	0	1	9	6	5	4	2	7	10

5.2. Simulation Results and Analysis

Thirty simulation runs were performed on three optimization algorithms (GAPSO-K, PSO-K, and K-means) using MATLAB. The initial parameter settings for the algorithms are shown in Table 2. The optimal simulation results are presented in Table 3.

Table 2. GAPSO-K parameters

parameter type	taking values
N	20
d	1
ger	300
limit	[1,50]
vlimit	[-1.5,1.5]
$w_{\max}$	0.9
$w_{\min}$	0.1
c_1	0.5
c_2	0.5
p_m	0.1
p_c	0.6
K	5

Table 3. Optimized gauge number assignment

Sorting area code q	Optimized product specification distribution		
	K-means	PSO-K	GAPSO-K
1	23、8、25、43 24、41、22、40 46、7	16、22、28、26 2、7、31、25 38、46	16、22、26、2 7、31、25、38 43、35
2	19、12、30、49 50、14、13、35 6、9	27、8、15、32 36、39、50、48 6、30	29、3、42、45 23、49、1、37 4、12
3	29、3、44、45 38、1、37、15 18、10	14、44、10、17 20、18、41、19 21、24	28、13、50、46 34、47、11、33 24、9
4	31、42、34、32 36、5、48、21 20、28	40、35、12、1 34、9、33、13 11、5	27、8、15、32 36、39、48、6 30、21
5	26、11、16、27 17、33、39、4 47、2	29、3、42、45 23、49、37、4 43、47	14、40、44、10 17、20、18、41 19、5

A 1:1 digital twin of the sorting system workflow was constructed using EM-Plant software, with parametric configurations rigorously aligned to real-world operational requirements. Each system component—including material handling devices and sorting mechanisms—was endowed with physics-based operational parameters and control logic emulation derived from actual system protocols. Customized control strategies were algorithmically encoded to replicate the decision-making framework of the physical sorting system.

The specification allocation schemes generated by the three aforementioned algorithms were subjected to comparative validation within this simulation environment. Figure 5 illustrates the 2D schematic representation of the integrated sorting system, comprising modular subsystems:

- Replenishment trolleys
- Horizontal sorting machines
- Vertical sorting units
- Conveyor assemblies
- Buffer zones
- Packaging units

High parametric fidelity was ensured through meticulous calibration of equipment specifications, throughput rates, and material flow dynamics in EM-Plant. This digital-physical correlation enables the simulation platform to effectively evaluate allocation strategies under quasi-real operational conditions. Through iterative simulation cycles, optimized specification distribution schemes were derived, demonstrating measurable reductions in total order processing time. The computational framework thus provides a validated mechanism for balancing system throughput and resource utilization efficiency prior to physical implementation.

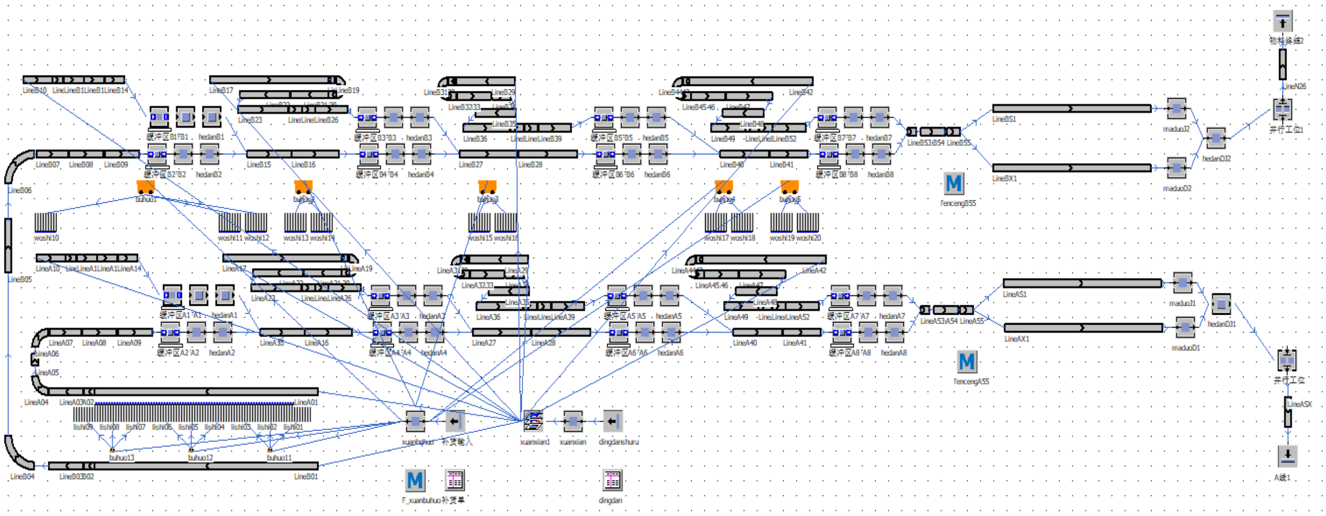

Figure 5. Two-dimensional model of composite integrated sorting system

The site layout consists of three integrated sorting lines and one special-shaped cigarette sorting line. This study primarily focuses on the impact of the vertical machine's product distribution on the total order processing time, and therefore, the special-shaped cigarette sorting line is selected for analysis. Each sorting zone represents a sub-line of the special-shaped cigarette sorting line, as shown in Figure 6. The site utilizes five sub-lines for the special-shaped cigarettes, and thus, the number of zones discussed in this paper is also five. The entire special-shaped cigarette sorting line model is composed of vertical machines, conveyors, buffer zones, merging areas, and packaging machines. Due to the layout conditions at the site, the conveyor lengths for each sub-line are different, and the conveyor length is simulated in EM-Plant to represent this variation.

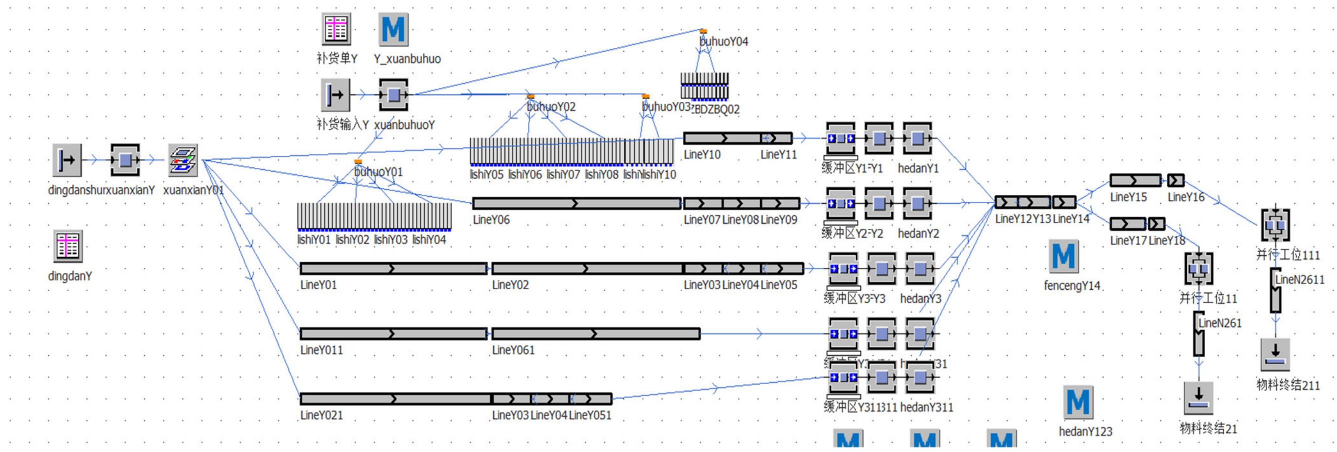

Figure 6. Shaped cigarette sorting line model

After optimization using the three algorithms, the average value of M for the PSO dynamic clustering algorithm increased by 10.2% compared to the dynamic clustering algorithm, while the average value of M for the GAPSO dynamic clustering algorithm increased by 15.2% compared to the dynamic clustering algorithm. In terms of the optimized T values, the average value of the particle swarm optimization (PSO) dynamic clustering algorithm improved by 12.5% compared to the dynamic clustering algorithm, and the average value of the genetic algorithm-based particle swarm optimization (GAPSO) dynamic clustering algorithm improved by 16.4%. Since the GAPSO dynamic clustering algorithm is an improvement based on the PSO dynamic clustering algorithm, both optimization algorithms share certain similarities, with the improvement over the PSO dynamic clustering algorithm being only 5.6%. Therefore, the product distribution results obtained using the GAPSO dynamic clustering algorithm are the most optimal, significantly reducing the total order processing time and improving sorting efficiency.

The evolutionary process of the optimal values for the product similarity coefficient of the three algorithms in the MATLAB simulation results is shown in Figure 7.

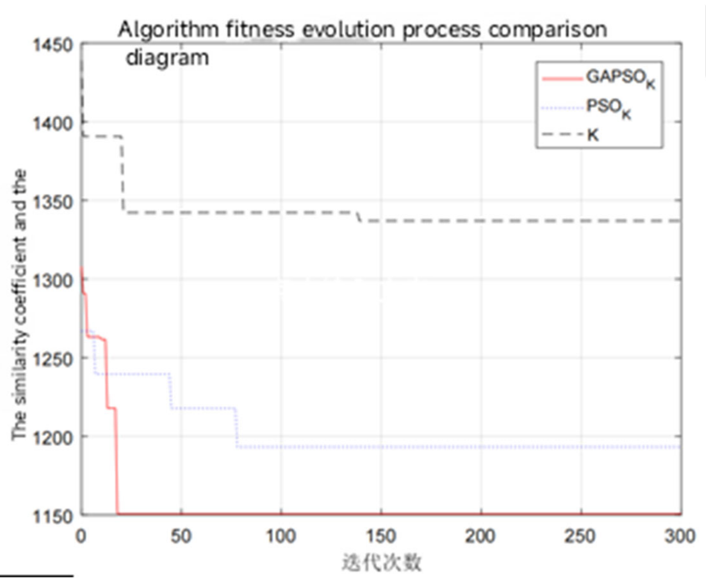

Figure 7. GAPSO-K, PSO-K, K-means comparison chart

The Genetic Particle Swarm K-means Clustering Algorithm (GAPSO-K) converged after 18 iterations with a value of 1150; the Particle Swarm K-means Clustering Algorithm (PSO-K) converged after 78 iterations with a value of 1193, and the K-means Clustering Algorithm (Kmeans) converged after 139 iterations with a value of 1337. The Genetic Particle Swarm K-means Clustering Algorithm (GAPSO-K) achieved the optimal convergence result with the fewest iterations, demonstrating significantly better performance compared to the other two algorithms. Moreover, verification through the EM-Plant software confirmed that the product distribution obtained using this algorithm resulted in a significantly lower total order processing time compared to the other two algorithms.

6. Summary

This study investigates specification allocation optimization in flexible logistics sorting systems by establishing a specification clustering model using the similarity coefficient as the fitness function. An innovative genetic-particle swarm optimization (GAPSO-K) dynamic clustering algorithm is proposed to solve the model. To enhance the fitness function's responsiveness to practical sorting demands, the model integrates sorting volume and condition number adjustments into the specification coefficient calculation. Genetic crossover and mutation operations are incorporated into the algorithm to expand solution space exploration and improve population diversity. Numerical solutions were derived using MATLAB, with comparative case studies validating the algorithm's superior adaptability to specification allocation challenges.

Leveraging empirical data from a tobacco logistics case, system simulations in EM-Plant demonstrated significant efficiency gains. The GAPSO-K algorithm reduced total order processing time to 252.7 seconds, achieving 16.4% and 5.6% improvements over K-means and PSO-K algorithms, respectively, from a baseline of 302.4 seconds. These results confirm the efficacy of the proposed hybrid algorithm in optimizing specification allocation for flexible sorting systems, offering a novel approach to enhance logistics efficiency.

Research Limitations and Future Directions

While this work focused on vertical sorting machine allocation as the primary efficiency determinant, horizontal sorting machine configuration—an equally critical factor in flexible logistics systems—remains unaddressed. Future studies should investigate horizontal machine allocation mechanisms to achieve comprehensive system optimization.

Methodological Contributions

The integration of genetic operations with swarm intelligence establishes a robust framework for balancing global exploration and local exploitation, advancing the state-of-the-art in adaptive logistics system design.

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